Elements of Human Decision-Making

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Abstract

The purpose of this paper is to present some understandings of the human problem-solving activity that we have gained in the Collaborative Agent Design Research Center (CADRC) over the past two decades. Since we feel strongly that the human decision-maker should be an integral component of any computer-based decision-support system, it follows that we would have endeavored to incorporate many of the elements that appear to be important to the user in the design of these systems. The complexity of the human cognitive system is evidenced by the large body of literature that describes problem-solving behavior and the relatively fewer writings that attempt to provide comprehensive explanations of this behavior. Our contributions in this field are confined to the identification of important elements of the problem-solving activity and exploration of how these elements might influence the design of a decision-support system.

Keywords

agents, analysis, communication, computers, context, data, data-centric, decisions, decision-making, decision-support, design, evaluation, information, information-centric, intuition, problem-solving, reasoning, representation, synthesis, visualization

Some Human Problem Solving Characteristics

Human beings are inquisitive creatures by nature who seek explanations for all that they observe and experience in their living environment. While this quest for understanding is central to our success in adapting to a changing and at times unforgiving environment, it is also a major cause for our willingness to accept partial understandings and superficial explanations when the degree of complexity of the problem situation confounds our mental capabilities. In other words, a superficial or partial explanation is considered better than no explanation at all. As flawed as this approach may be, it has helped us to solve difficult problems in stages. By first oversimplifying a problem we are able to develop an initial solution that is later refined as a better understanding of the nature of the problem evolves. Unfortunately, now we have to contend with another characteristic of human beings, our inherent resistance to change and aversion to risk taking. Once we have found an apparently reasonable and workable explanation or solution we tend to lose interest in pursuing its intrinsic shortcomings and increasingly believe in its validity. Whether driven by complacency or lack of confidence, this state of affairs leads to many surprises. We are continuously discovering that what we believed to be true is only partly true or not true at all, because the problem is more complicated than we had previously assumed it to be.

The complexity of problems faced by human society in areas such as management, economics, marketing, engineering design, and environmental preservation, is increasing for several reasons. First, computer-driven information systems have expanded these areas from a local to an increasingly global focus. Even small manufacturers are no longer confined to a regionally localized market for selling their products. The marketing decisions that they have to make must take into account a wide range of factors and a great deal of knowledge that is far removed from the local environment. Second, as the net-centricity of the problem system increases so do the relationships among the various factors. These relationships are difficult to deal with, because they require the decision-maker to consider many factors concurrently. Although the biological operation of the human brain is massively parallel, our conscious reasoning processes are sequential. Simply stated, we have difficulty reasoning about more than two or three variables at any one time. Third, as the scope of problems increases decision-makers suffer simultaneously from two diametrically opposed but related conditions. They tend to be overwhelmed by the shear volume of data that they have to consider, and yet they lack information in many specific areas. To make matters worse, the information tends to change dynamically in largely unpredictable ways

It is therefore not surprising that governments, corporations, businesses, down to the individual person, are increasingly looking to computer-based decision-support systems for assistance. This has placed a great deal of pressure on software developers to rapidly produce applications that will overcome the apparent failings of the human decision-maker. While the expectations have been very high, the delivery has been much more modest. The expectations were simply unrealistic. It was assumed that advances in technology would be simultaneously accompanied by an understanding of how these advances should be applied optimally to assist human endeavors. History suggests that such an a priori assumption is not justified. There are countless examples that would suggest the contrary. For example, the invention of new materials (e.g., plastics) has inevitably been followed by a period of misuse. Whether based on a misunderstanding or lack of knowledge of its intrinsic properties, the new material was typically initially applied in a manner that emulated the material(s) it replaced. In other words, it took some time for the users of the new material to break away from the existing paradigm. A similar situation currently exists in the area of computer-based decision-support systems.

The Rationalistic Tradition

To understand current trends in the evolution of progressively more sophisticated decision-support systems it is important to briefly review the foundations of problem solving methodology from an historical perspective. Epistemology is the study or theory of the origin, nature, methods and limits of knowledge. The dominant epistemology of Western Society has been technical rationalism (i.e., the systematic application of scientific principles to the definition and solution of problems).

The rationalistic approach to a problem situation is to proceed in well defined and largely sequential steps as shown in Figure 1: define the problem; establish general rules that describe the relationships that exist in the problem system; apply the rules to develop a solution; test the validity of the solution; and, repeat all steps until an acceptable solution has been found. This simple view of problem solving suggested a model of sequential decision-making that has retained a dominant position to the present day. With the advent of computers it was readily embraced by 1st Wave software (Figure 2) because of the ease with which it could be translated into decision-support systems utilizing the procedural computer languages that were available at the time.

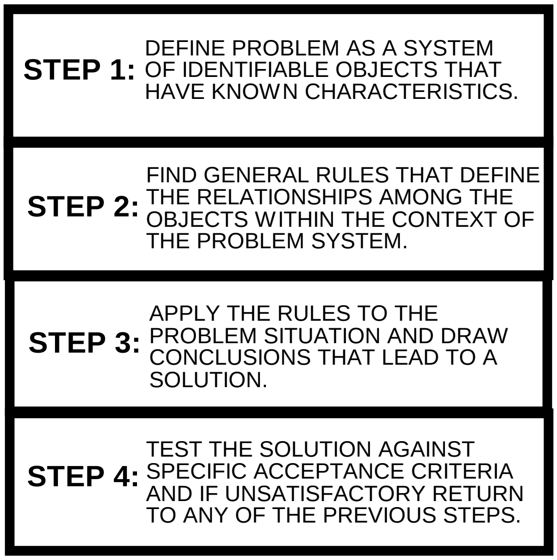

Figure 1: Solution of simple problems

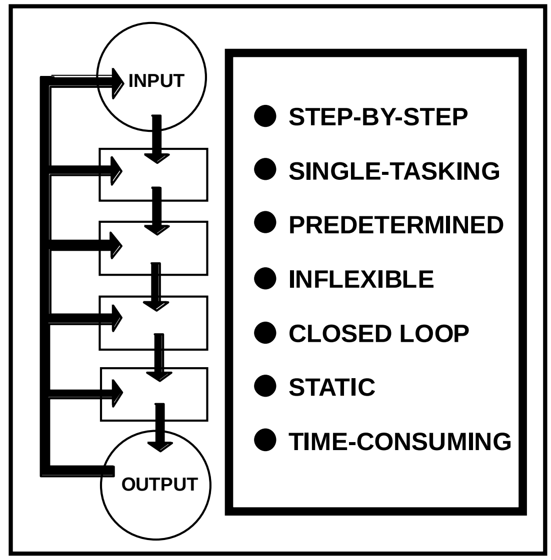

Figure 2: Sequential decision-support

The close correlation between the rationalistic approach and what is commonly referred to as the scientific method, is readily apparent in the series of basic steps that are employed in scientific investigations: observe the phenomenon that requires explanation; formulate a possible explanation; develop a method capable of predicting or generating the observed phenomenon; interpret the results produced by the method; and, repeat all steps until an acceptable explanation of the observed phenomenon has been found. Scientific research typically attempts to establish situations in which observable actions (or reactions) are governed by a small number of variables that can be systematically manipulated. Every effort is made to keep the contrived situation simple, clear and deterministic, so that the results of the simulation can be verified.

However, natural phenomena and real world problems are often very complex involving many related variables. Neither the relationships among the variables nor the variables themselves are normally sufficiently well understood to provide the basis for clear and comprehensive definitions. In other words, problem situations are often too complex to be amenable to an entirely logical and predefined solution approach. Under these circumstances the analytical strategy has been to decompose the whole into component parts, as follows:

- ♦ Decompose the problem system into sub-problems.
- ♦ Study each sub-problem in relative isolation, using the rationalistic approach (Figure 1). If the relationships within the sub-problem domain cannot be clearly defined then decompose the sub-problem further.
- ♦ Combine the solutions of the sub-problems into a solution of the whole.

Underlying this problem-solving strategy is the implicit assumption that an understanding of parts leads to an understanding of the whole. Under certain conditions this assumption may be valid. However, in many complex problem situations the parts are tightly coupled so that the behavior of the whole depends on the interactions among the parts rather than the internal characteristics of the parts themselves (Bohm 1983, Senge 1993). An analogy can be drawn with the behavior of ants. Each ant has only primitive skills, such as the ability to interpret the scent of another ant and the instinctive drive to search for food, but little if any notion of the purpose or objectives of the ant colony as a whole. In other words, an understanding of the behavior of an individual ant does not necessarily lead to an understanding of the community behavior of the ant colony of which the ant is a part.

Decomposition is a natural extension of the scientific approach to problem solving and has become an integral and essential component of rationalistic methodologies. Nevertheless, it has serious limitations. First, the behavior of the whole usually depends more on the interactions of its parts and less on the intrinsic behavior of each part. Second, the whole is typically a part of a greater whole and to understand the former we have to also understand how it interacts with the greater whole. Third, the definition of what constitutes a part is subject to viewpoint and purpose, and not intrinsic in the nature of the whole. For example, from one perspective a coffee maker may be considered to comprise a bowl, a hotplate, and a percolator. From another perspective it consists of electrical and constructional components, and so on.

Rationalism and decomposition are certainly useful decision-making tools in complex problem situations. However, care must be taken in their application. At the outset it must be recognized that the reflective sense (Schon 1983) and intuition of the decision-maker are at least equally important tools. Second, decomposition must be practiced with restraint so that the complexity of the interactions among parts is not overshadowed by the much simpler behavior of each of the individual parts. Third, it must be understood that the definition of the parts is largely dependent on the objectives and knowledge about the problem that is currently available to the decision-maker. Even relatively minor discoveries about the greater whole, of which the given problem situation forms a part, are likely to have significant impact on the purpose and the objectives of the problem situation itself.

Decision Making in Complex Problem Situations

As shown in Figure 3, there are several characteristics that distinguish a complex problem from a simple problem. First, the problem is likely to involve many related issues or variables. As discussed earlier the relationships among the variables often have more bearing on the problem situation than the variables themselves. Under such tightly coupled conditions it is often not particularly helpful, and may even be misleading, to consider issues in isolation. Second, to confound matters some of the variables may be only partially defined and some may yet to be discovered. In any case, not all of the information that is required for formulating and evaluating alternatives is available. Decisions have to be made on the basis of incomplete information.

Third, complex problem situations are pervaded with dynamic information changes. These changes are related not only to the nature of an individual issue, but also to the context of the problem situation. For example, a change in wind direction during a major brushfire may have a profound impact on the entire nature of the relief operation. Apart from precipitating an immediate re-evaluation of the firefighting strategy, it may require the relocation of firefighters and their equipment, the replanning of evacuation routes, and possibly even the relocation of distribution centers. Certainly, a change in the single factor of wind direction could, due to its many relationships, call into question the very feasibility of the existing course of action (i.e., the firefighting plan). Even under less critical conditions it is not uncommon for the solution objectives to change several times during the decision-making process. This fourth characteristic of complex problem situations is of particular interest. It exemplifies the tight coupling that can exist among certain problem issues, and the degree to which decision-makers must be willing to accommodate fundamental changes in the information that drives the problem situation.

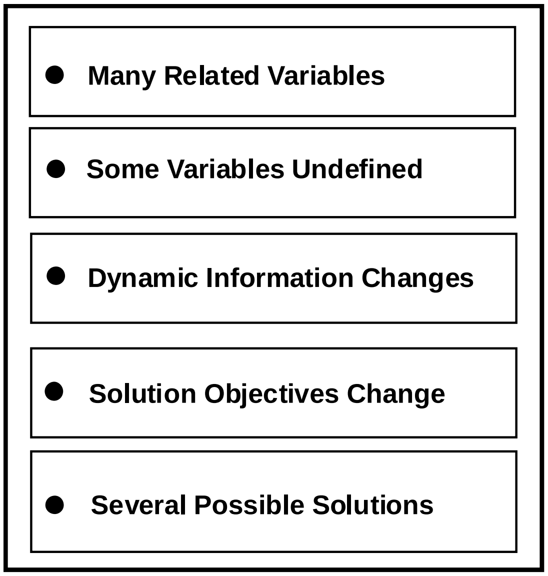

Figure 3: Character of complex problems

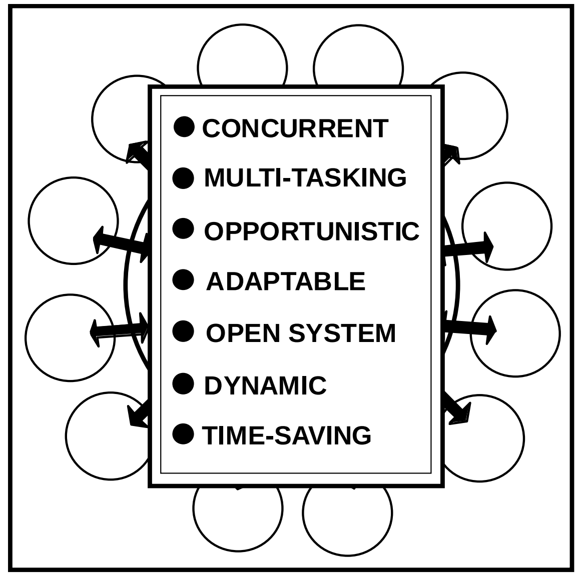

Figure 4: Parallel decision-support

Fifth, complex problems typically have more than one solution (Archea 1987). It is usually fruitless to look for an optimum solution, because there are no static benchmarks available for evaluating optimality. A solution is found to be acceptable if it satisfies certain performance requirements and if it has been determined that the search for alternatives is no longer warranted. Such a determination is often the result of resource constraints (e.g., availability of time, penalty of non-action, or financial resources) rather than a high level of satisfaction with the quality of the proposed solution.

While human decision-making in complex problem situations has so far defied rigorous scientific explanation, we do have knowledge of at least some of the characteristics of the decision-making activity.

- Decision-makers typically define the problem situation in terms of issues that are known to impact the desired outcome. The relative importance of these issues and their relationships to each other change dynamically during the decision-making process. So also do the boundaries of the problem space and the goals and objectives of the desired outcome. In other words, under these circumstances decision-making is an altogether dynamic process in which both the rules that govern the process and the required properties of the end-result are subject to continuous review, refinement and amendment.

- The complexity of the decision-making activity does not appear to be due to a high level of difficulty in any one area but the multiple relationships that exist among the many issues that impact the desired outcome. Since a decision in one area will tend to influence several other areas there is a need to consider many factors at the same time. This places a severe burden on the human cognitive system. Although the neurological mechanisms that support conscious thought processes are massively parallel, the operation of these reasoning capabilities is largely sequential. Accordingly, decision-makers tend to apply simplification strategies for reducing the complexity of the problem-solving activity. In this regard it becomes readily apparent why 2nd Wave software provides a much more useful architecture for decision-support systems (Figure 4).

- Observation of decision-makers in action has drawn attention to the important role played by experience gained in past similar situations, knowledge acquired in the general course of decision-making practice, and expertise contributed by persons who have detailed specialist knowledge in particular problem areas. The dominant emphasis on experience is confirmation of another fundamental aspect of the decision-making activity. Problem-solvers seldom start from first principles. In most cases, the decision-maker builds on existing solutions from previous situations that are in some way related to the problem under consideration. From this viewpoint, the decision-making activity involves the modification, refinement, enhancement and combination of existing solutions into a new hybrid solution that satisfies the requirements of the given problem system. In other words, problem-solving can be described as a process in which relevant elements of past prototype solution models are progressively and collectively molded into a new solution model. Very seldom are new prototype solutions created that do not lean heavily on past prototypes.

- Finally, there is a distinctly irrational aspect to decision-making in complex problem situations. Donald Schon refers to a "...reflective conversation with the situation...". (Schon 1983). He argues that decision-makers frequently make value judgments for which they cannot rationally account. Yet, these intuitive judgments often result in conclusions that lead to superior solutions. It would appear that such intuitive capabilities are based on a conceptual understanding of the situation, which allows the problem solver to make knowledge associations at a highly abstract level.

Based on these characteristics the solution of complex problems can be categorized as an information intensive activity that depends for its success largely on the availability of information resources and, in particular, the experience and reasoning skills of the decision-makers. It follows that the quality of the solutions will vary significantly as a function of the problem-solving skills, knowledge, and information resources that can be brought to bear on the solution process. This clearly presents an opportunity for the useful employment of computer-based decision-support systems in which the capabilities of the human decision-maker are complemented with knowledge bases, expert agents, and self-activating conflict identification and monitoring capabilities.

Principal Elements of Decision-Making

Over the past two decades that the CADRC Center has been developing distributed, collaborative decision-support systems some insights have been gained into the nature of the decision-making activity. In particular, we have found it useful to characterize decision-making in terms of six functional elements (Figure 5): ***information***; ***representation***; ***visualization***; ***communication***; ***reasoning***; and, ***intuition***.

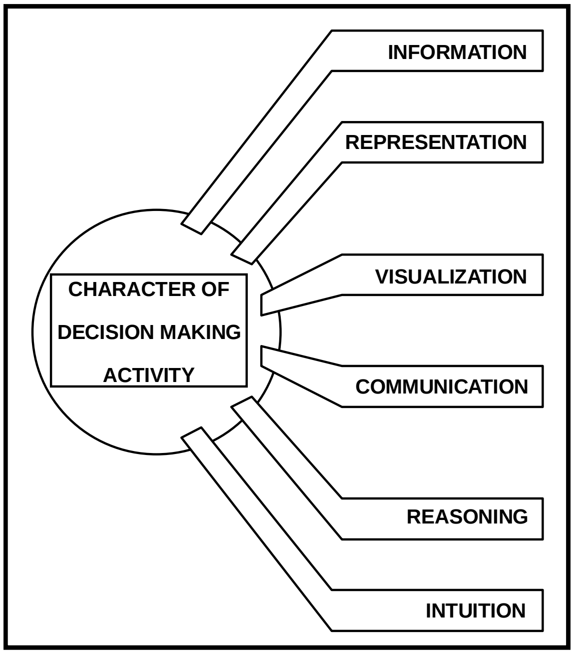

Figure 5: Decision-making elements

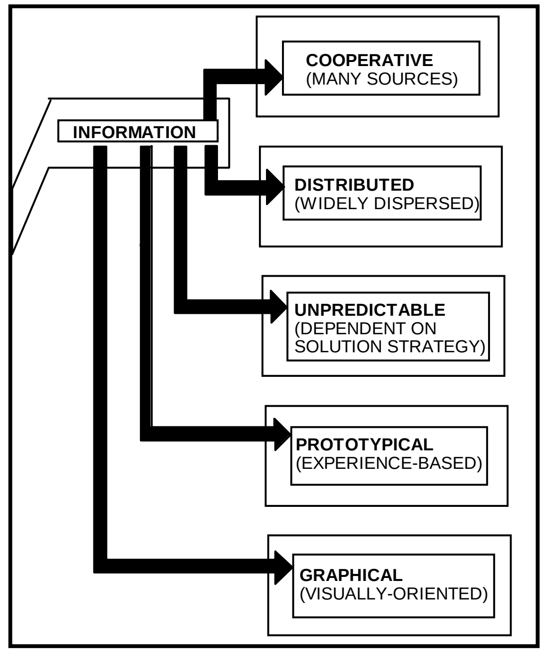

Figure 6: The ***information*** element

The *Information* Element

Decision-making in complex problem situations is a collaborative activity involving many sources of information that are often widely dispersed. Seldom is all of the information required for the solution, or even only a component of the problem, physically located in the immediate vicinity of the decision-maker. In fact, much of the information is likely to reside in remote repositories that can be accessed only through electronic means, the telephone, e-mail, or the temporary relocation of a member of the problem-solving team (Figure 6). If the desired information requires expert advice the services of a consultant may be required in addition to, or instead of, access to an information resource.

The term *information* is used here in the broadest sense to include not only factual data and the progressively more comprehensive and detailed description of the problem system, but also the many knowledge bases that are part of the local and global environment within which the problem situation is constituted. In this regard, we are concerned with the knowledge of the individual members of the problem-solving team, the knowledge of peripheral players (e.g., colleagues, associates and consultants), the collective knowledge of the profession (such as the various engineering professions, the military establishment, or the management profession) and industry, and beyond that those aspects of what might be referred to as global knowledge that impact the problem context.

Typically, the problem specifications (i.e., constraints, criteria, and objectives) evolve with the problem solution as the decision-makers interact with the problem situation. Accordingly, the information requirements of the problem solver are not predictable since the information needed to solve the problem depends largely on the solution strategy adopted (Fischer and Nakakoji 1991). In this respect problem solving is a learning process in which the decision-maker progressively develops a clearer understanding of the problem that is required to be solved.

Much of the information that decision-makers use in the development of a problem solution is gleaned from experience with past projects. In fact, it can be argued that solutions commonly evolve out of the adaptation, refinement and combination of prototypes (Gero et al. 1988). This argument suggests that the more expert human decision-makers are the more they tend to rely on prototypical information in the solution of complex problems. It would appear that the accumulation, categorization and ability to apply prototype knowledge are the fundamental requirements for a human decision-maker to reach the level of *expert* in a particular domain. Based largely on the work of Gero et al. (1988) and Rosenman and Gero (1993) the following techniques used by engineering designers to develop solutions through the manipulation of prototypes can be identified as being universally applicable to other problem domains:

- ***Refinement:*** The prototype can be applied after changes have been made in the values of parameter variables only (i.e., the instance of the prototype is reinterpreted within the acceptable range of the parameter variables).
- ***Adaptation:*** Application of the prototype requires changes in the parameters that constitute the description of the prototype instance, based on factors that are internal to the prototype (i.e., a new prototype instance is produced).
- ***Combination:*** Application of the prototype requires the importation of parameter variables of other prototypes, producing a new instance of a reinterpreted version of the original prototype.
- ***Mutation:*** Application of the prototype requires structural changes to the parameter variables, either through internal manipulations or the importation of parameter variables from external sources (i.e., either a reinterpreted version of the original prototype or a new prototype is produced).
- ***Analogy:*** Creation of a new prototype based on a prototype that exists in another context, but displays behavioral properties that appear to be analogous to the application context.

For application purposes in knowledge-based decision-support systems prototypes may be categorized into five main groups based on knowledge content (Schon 1988, Pohl and Myers 1994):

1. **Vertica**l prototype knowledge bases that contain typical object descriptions and relationships for a complete problem situation or component thereof. Such a knowledge base may include all of the types that exist in a particular problem setting, for example: an operational template for a particular kind of humanitarian relief mission; a certain type of propulsion unit; or, a building type such as a library, sports stadium, or supermarket.
2. **Horizontal** prototype knowledge bases that contain typical solutions for sub-problems such as commercial procurement practices, construction of a temporary shelter, or techniques for repairing equipment. This kind of knowledge often applies to more than one discipline. For example, the techniques for repairing a truck apply equally to the military as they do to auto-repair shops, engineering concerns, and transportation related organizations.

3. **Domain** prototype knowledge bases that contain guidelines for developing solutions within contributing narrow domains. For example, the range of structural solutions appropriate for the construction of a suspension bridge during a military mission is greatly influenced by the availability of material, the prevailing wind conditions, and the time available for erection. Posed with this design problem military engineers will immediately draw upon a set of rules that guide the design activity.
4. **Exemplar** prototype knowledge bases that describe a specific instance of an object type or solution to a sub-problem. Exemplary prototypes can be instances of vertical or horizontal prototypes, such as a particular building type or a method of welding a certain kind of steel joint that is applied across several disciplines and industries (e.g., building industry and automobile industry). Decision-makers often refer to exemplary prototypes in exploring solution alternatives to sub-problems.
5. **Experiential** knowledge bases that represent the factual prescriptions, strategies and solution conventions employed by the decision-maker in solving similar kinds of problem situations. Such knowledge bases are typically rich in methods and procedures. For example, a particularly memorable experience such as the deciding event in a past business negotiation or the experience of seeing for the first time the magnificent sail-like concrete shell walls of the Sydney Opera House, may provide the basis for a solution method that is applied later to create a similar experience in a new problem situation that may be quite different in most other respects. In other words, experiential prototypes are not bound to a specific type of problem situation. Instead, they represent techniques and methods that can be reproduced in various contexts with similar results. Experiential knowledge is often applied in very subtle ways to guide the solution of sub-problems (e.g., a subterfuge in business merger or take-over negotiations that is designed to mislead a competing party).

The amount of prototypical information is potentially overwhelming. However, the more astute and experienced decision-maker will insist on taking time to assimilate as much information as possible into the problem setting before committing to a solution theme. There is a fear that early committal to a particular solution concept might overlook characteristics of the problem situation that could gain in importance in later stages, when the solution has become too rigid to adapt to desirable changes. This reluctance to come to closure places a major information management burden on the problem solver. Much of the information cannot be specifically structured and prepared for ready access, because the needs of the problem solver cannot be fully anticipated. Every step toward a solution generates new problems and information needs (Simon 1981).

The *Representation* Element

The methods and procedures that decision-makers utilize to solve complex problems rely heavily on their ability to identify, understand and manipulate objects (Figure 7). In this respect, objects are complex symbols that convey meaning by virtue of the explicit and implicit information that they encapsulate within their domain. For example, military strategists develop operational plans by reasoning about terrain, weather conditions, enemy positions, weapon assets, and so on. Each of these objects encapsulates knowledge about its own nature, its relationships with other objects, its behavior within a given environment, what it requires to meet its own performance objectives, and how it might be manipulated by the decision-maker within a given problem scenario (Figure 8). This knowledge is contained in the various representational forms of the object as factual data, relationships, algorithms, rules, exemplar solutions, and prototypes.

The reliance on object representations in reasoning endeavors is deeply rooted in the innately associative nature of the human cognitive system. Information is stored in long-term memory through an indexing system that relies heavily on the forging of association paths. These paths relate not only information that collectively describes the meaning of symbols such as building, car, chair, and tree, but also connect one symbol to another. The symbols themselves are not restricted to the representation of physical objects, but also serve as concept builders. They provide a means for grouping and associating large bodies of information under a single conceptual metaphor. In fact, Lakoff and Johnson (1980) argue that *"...our ordinary conceptual system, in terms of which we both think and act, is fundamentally metaphorical in nature."* They refer to the influence of various types of metaphorical concepts, such as *"…desirable is up"* (i.e., spatial metaphors) and *"…fight inflation"* (i.e., ontological or human experience metaphors), as the way human beings select and communicate strategies for dealing with everyday events.

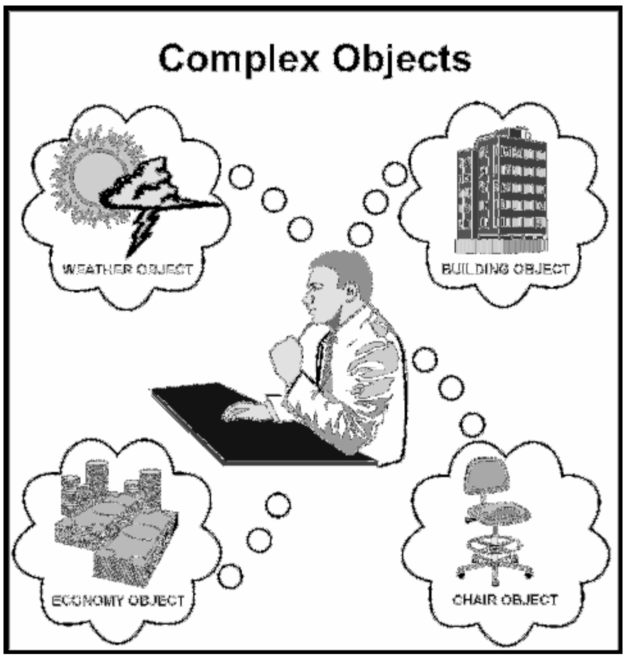

Figure 7: Symbolic reasoning with objects

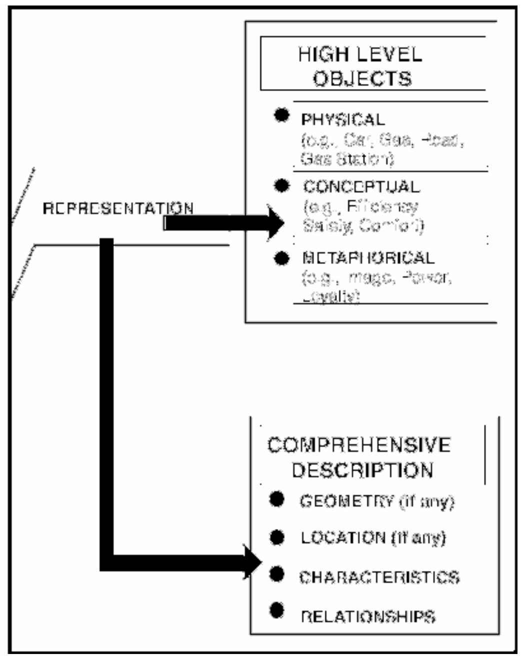

Figure 8: The ***representation*** element

Problem-solvers typically intertwine the factually based aspects of objects with the less precise, but implicitly richer language of metaphorical concepts. This leads to the spontaneous linkage of essentially different objects through the process of analogy. In other words, the decision-maker recognizes similarities between two or more sub-components of apparently unrelated objects and embarks upon an exploration of the discovered object seeking analogies where they may or may not exist. At times these seemingly frivolous pursuits lead to surprising and useful solutions of the problem at hand.

The need for a high level representation is fundamental to all computer-based decision-support systems. It is an essential prerequisite for embedding artificial intelligence in such systems, and forms the basis of any meaningful communication between user and computer. Without a high level representation facility the abilities of the computer to assist the human decision maker are confined to the performance of menial tasks, such as the automatic retrieval and storage of data or the computation of mathematically defined quantities. While even those tasks may be highly productive they cannot support a partnership in which human users and computer-based systems collaborate in a meaningful and intelligent manner in the solution of complex problems.

The term *high level representation* refers to the ability of computer software to process and interpret changes in data within an appropriate context. It is fundamental to the distinction between data-centric and information-centric software. Strictly speaking data are numbers and words without relationships[1]. Software that incorporates an internal representation of data only is often referred to as *data-centric* software. Although the data may be represented as objects the absence of relationships to define the functional purpose of the data inhibits the inclusion of meaningful and reliable automatic reasoning capabilities. Data-centric software, therefore, must largely rely on predefined solutions to predetermined problems, and has little (if any) scope for adapting to real world problems in near real-time.

Information, on the other hand, refers to the combination of data with relationships to provide adequate context for the interpretation of the data. The richer the relationships, the greater the context and the more opportunity for automatic reasoning by software agents. Software that incorporates an internal information model (i.e., ontology) consisting of objects, their characteristics, and the relationships among those objects is often referred to as *information-centric* software. The information model provides a virtual representation of the real world domain under consideration. Since information-centric software has some *understanding* of what it is processing it normally contains tools rather than predefined solutions to predetermined problems. These software tools are commonly referred to as agents that collaborate with each other and the human user(s) to develop solutions to problems in near real-time, as they occur.

The *Visualization* Element

Problem solvers use various visualization media, such as visual imagination, drawings and physical models, to communicate the current state of the evolving solution to themselves and to others (Figure 9). Drawings, in particular, have become intrinsically associated with problem solving. Although the decision-maker can reason about complex problems solely through mental processes, drawings and related physical images are useful and convenient for extending those processes. The failings of the drawing as a vehicle for communicating the full intent of the decision-maker do not apply to the creator of the drawing. To the latter the drawing serves not only as an extension of long-term memory, but also as a visual bridge to its associative indexing structure. In this way, every meaningful part of the drawing is linked to related data and deliberation sequences that together provide an effectively integrated and comprehensive representation of the artifact.

From a technical point of view a great deal of headway has been made over the past two decades in the area of computer-based visualization. However, without high-level representation capabilities even the most sophisticated computer generated images are nothing but hollow shells. If the computer system does not have even the simplest understanding of the nature of the

[1] Even though data are often stored in a relational database management system, the relationships that are stored with the data in such a database are structural in nature and do not provide any information on how the data will be used (i.e., the *context* of the data).

objects that are contained in the image then it cannot contribute in any way to the analysis of those objects. On the other hand, visualization in combination with high-level representation becomes the most powerful element of the user-interface of a decision-support system. Under these circumstances, visualization promotes the required level of understanding between the user and the computer as they collaborate in the solution of a problem.

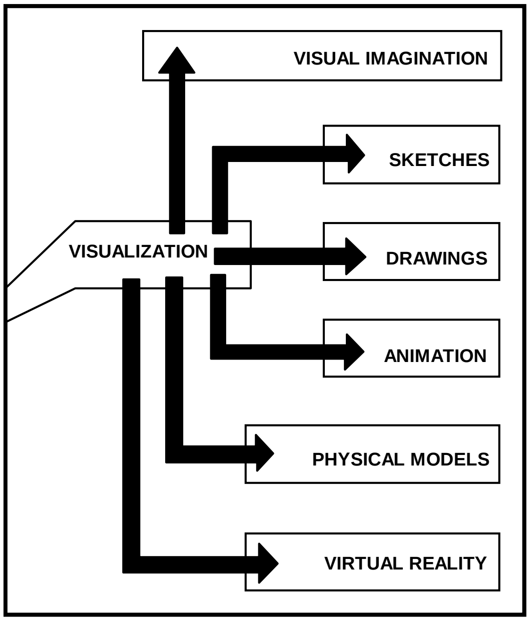

Figure 9: The ***visualization*** element

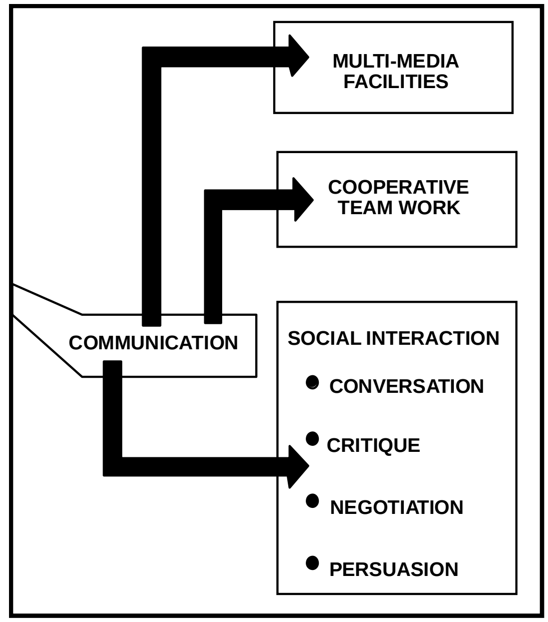

Figure 10: The ***communication*** element

The *Communication* Element

The solution of complex problems is typically undertaken by a team of decision-makers. Each team member contributes within a collaborative decision-making environment that relies heavily on the normal modes of social interaction, such as conversation, critique, negotiation, and persuasion (Figure 10). Two aspects of such an interactive environment are particularly well catered for in computer-based systems. The first aspect relates to the ability of computer-driven communication networks to link together electronically based resources located anywhere on Earth or in space. Technical advances in the communication industry have greatly enhanced the ability of individuals to gain access to remotely distributed information sources, and to interact with each other over vast distances. In fact, connectivity rather than geographical distance has become the principal determinant of communication.

The second aspect is interwoven with the first by relatively recent technological advances that have permitted all types of information to be converted into digital form. Through the use of digital switching facilities modern communication networks are able to transmit telephone conversations and graphical images in the same way as data streams have been sent from one computer to another over the past 40 years.

As a direct result of these advances in communication systems the convenient and timely interaction of all of the members of a widely dispersed problem-solving team is technically assured. It is now incumbent on software developers to produce computer-based decision-support systems that can fully support collaborative teamwork, which is neither geographically nor operationally limited. Such systems will integrate not only computer-based information resources and software agents, but also multiple human agents (i.e., the users) who will collaborate with the computer-based resources in a near real-time interactive environment.

The *Reasoning* Element

Reasoning is central to any decision-making activity. It is the ability to draw deductions and inferences from information within a problem-solving context. The ability of the problem solver to reason effectively depends as much on the availability of information, as it does on an appropriately high level form of object representation (Figure 11). Decision-makers typically define complex problems in terms of issues that are known to impact the desired outcome. The relative importance of these issues and their relationships to each other change dynamically during the decision-making process. So also do the boundaries of the problem space and the goals and objectives of the desired outcome. In other words, the solution of complex problems is an altogether dynamic process in which both the rules that govern the process and the required properties of the end-result are subject to continuous review, refinement and amendment (Reitman 1964 and 1965, Rittel and Weber 1984).

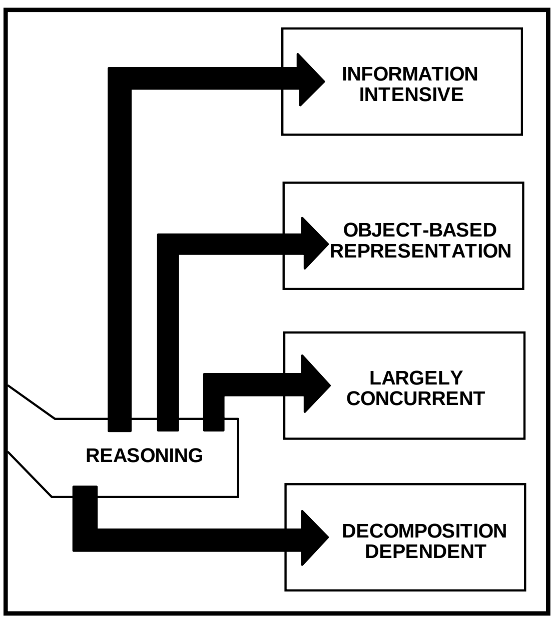

Figure 11: The ***reasoning*** element

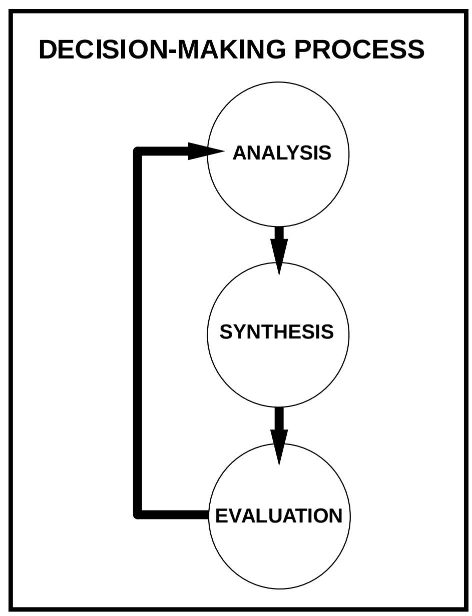

Figure 12: Reasoning methodology

As discussed previously, the complexity of a problem is normally not due to a high degree of difficulty in any one area but the multiple relationships that exist among the many issues that impact the desired outcome. Since a decision in one area will tend to influence several other areas there is a critical need for concurrency. However, the reasoning capabilities of the human problem solver are sequential in nature[2]. Accordingly, decision-makers find it exceedingly difficult to consider more than three or four issues at any one time. In an attempt to deal with the

[2] Reasoning is a logical process that proceeds in a step-by-step manner. In this respect reasoning is quite different from intuition, which allows humans to spontaneously come to conclusions that are neither consciously formulated nor explainable at the time of their first appearance.

concurrency requirement several strategies are commonly employed to reduce the complexity of the reasoning process to a manageable level.

- ***Constraint Identification:*** By sifting through the available information the problem-solver hopes to find overriding restrictions and limitations that will eliminate knowledge areas from immediate consideration.
- ***Decision Factor Weighting:*** By comparing and evaluating important problem issues in logical groupings, relative to a set of predetermined solution objectives, the decision-maker hopes to identify a smaller number of issues or factors that appear to have greater impact on the final solution. Again, the strategy is to reduce the size of the information base by early elimination of apparently less important considerations.
- ***Solution Conceptualization:*** By adopting early in the decision-making process a conceptual solution, the problem-solver is able to pursue a selective evaluation of the available information. Typically, the problem-solver proceeds to subdivide the decision factors into two groups, those that are compatible with the conceptual solution and those that are in conflict. By a process of trial and error, often at a superficial level, the problem-solver develops, adapts, modifies, re-conceives, rejects and, often, forces the preconceived concept into a final solution.

In complex problem situations reasoning proceeds in an iterative fashion through a cycle of *analysis*, *synthesis* and *evaluation* (Figure 12). During the *analysis* stage (Figure 13) the problem-solver interprets and categorizes information to establish the relative importance of issues and to identify compatibilities and incompatibilities among the factors that drive these issues.

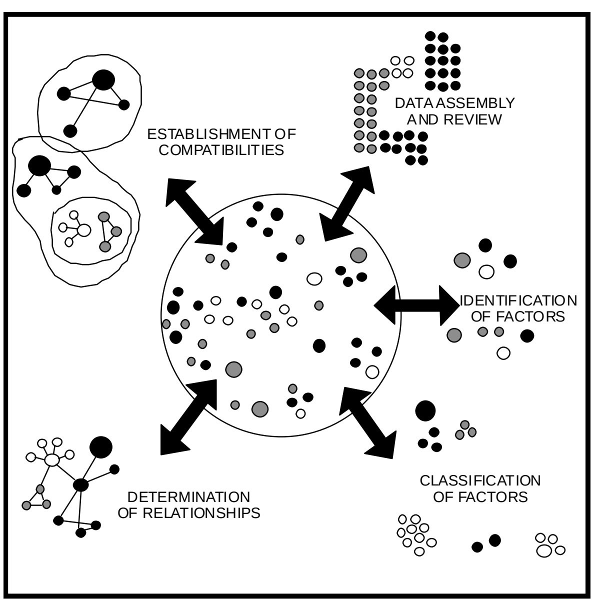

Figure 13: *Analysis* stage of reasoning

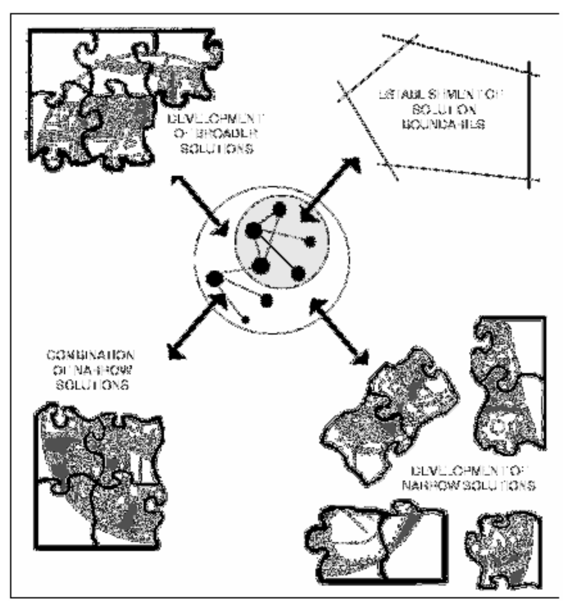

Figure 14: *Synthesis* stage of reasoning

During *synthesis* (Figure 14) solution boundaries and objectives are continuously reexamined as the decision-maker develops narrow solutions to sub-problems and combines these narrow solutions into broader solutions. Initially, these solution attempts are nothing more than trial balloons. Or, stated in more technical terms, explorations based on the development of the relationships among the principal issues and compatible factors identified during the *analysis* stage. Later, as the problem-solving activity progresses, firmer conceptual solution strategies with broader implications emerge. However, even during later cycles the solution strategies tend to be based on a limited number of issues or factors.

During the *evaluation* stage (Figure 15) the decision-makers are forced to test the current solution strategy with all of the known problem issues, some of which may have been considered only superficially or not at all during the formulation of the current solution proposal. This may require the current solution concepts to be modified, extended or altogether replaced. Typically, several solution strategies are possible and none are completely satisfactory. Archea (1987), in his description of the architectural design activity refers to this activity as *"... puzzle-making"*, suggesting by implication that the decision-maker utilizes the reasoning cycle more as a method for exploring the problem space than as a decision-making tool for forcing an early solution.

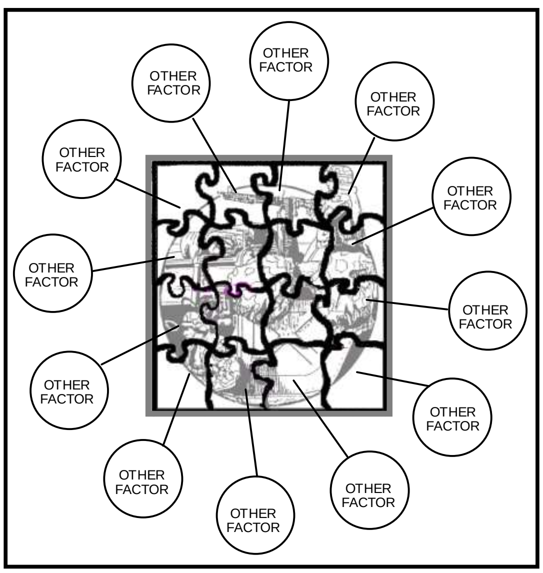

Figure 15: *Evaluation* stage of reasoning

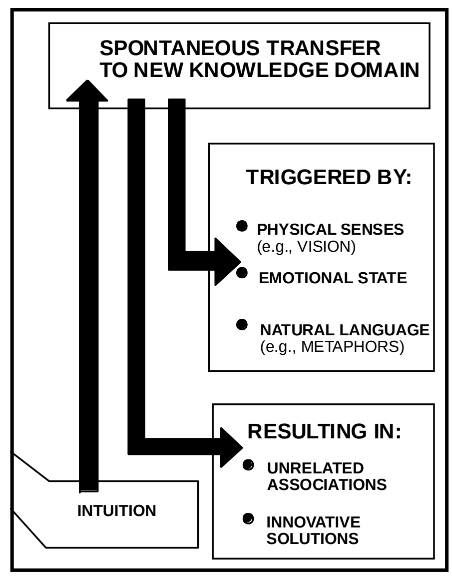

Figure 16: The ***intuition*** element

The *Intuition* Element

Donald Schon (1983 and 1988) has written extensively about the intuitive aspects of decision-making. Although he focused primarily on engineering design as an application area, his views provide valuable insight into the solution of complex problems in general. Design has all of the common characteristics of complex problem situations, and some additional ones such as the desire for solution uniqueness, that make it a prime candidate for computer-based assistance (Pohl et al.1994).

In Schon's (1988) view designers enter into *"... design worlds"* in which they find the objects, rules and prototype knowledge that they apply to the design problem under consideration. The implication is that the designer continuously moves in and out of design worlds that are triggered by internal and external stimuli. While the reasoning process employed by the designer in any particular design world is typically sequential and explicitly logical, the transitions from state to state are governed by deeper physiological and psychological causes. Some of these causes can be explained in terms of associations that the designer perceives between an aspect or element of the current state of the design solution and prototype knowledge that the designer has accumulated through experience. Others may be related to emotional states or environmental stimuli, or interactions of both (Figure 16).

For example, applying Schon's view to the broader area of complex problem solving, a particular aspect of a problem situation may lead to associations in the decision-maker's mind that are logically unrelated to the problem under consideration. However, when the decision-maker pursues and further develops these associations they sometimes lead to unexpected solutions. Typically, the validity of these solutions becomes apparent only after the fact and not while they are being developed. In popular terms we often refer to these solutions as *creative leaps* and label the author as a brilliant strategist. What we easily forget is that many of these intuitions remain unrelated associations and do not lead to any worthwhile result. Nevertheless, the intuitive aspect of decision-making is most important. Even if only a very small percentage of these intuitive associations were to lead to a useful solution, they would still constitute one of the most highly valued decision-making resources.

The reasons for this are twofold. First, the time at which the decision-maker is most willing to entertain intuitive associations normally coincides with a most difficult stage in the problem solving process. Typically, it occurs when an impasse has been reached and no acceptable solution strategy can be found. Under these circumstances intuition may be the only remaining course of action open to the decision-maker. The second reason is particularly relevant if there is a strong competitive element present in the problem situation. For example, during a chess game or during the execution of military operations. Under these circumstances, strategies and solutions triggered by intuitive associations will inevitably introduce an element of surprise that is likely to disadvantage the adversary.

The importance of the *intuition* element itself in decision-making would be sufficient reason to insist on the inclusion of the human decision-maker as an active participant in any computer-based decision system. In designing and developing such systems in the CADRC over the past decade we have come to appreciate the importance of the human-computer partnership concept, as opposed to automation. Whereas in some of our early systems (e.g., ICADS (Pohl et al. 1988) and AEDOT (Pohl et al. 1992)) we included agents that automatically resolve conflicts, today we are increasingly moving away from automatic conflict resolution to conflict detection and explanation. We believe that even apparently mundane conflict situations should be brought to the attention of the human agent. Although the latter may do nothing more than agree with the solution proposed by the computer-based agents, he or she has the opportunity to bring other knowledge to bear on the situation and thereby influence the final determination.

The Human-Computer Partnership

To look upon decision-support systems as partnerships between users and computers, in preference to automation, appears to be a sound approach for at least two reasons. First, the ability of the computer-based components to interact with the user overcomes many of the difficulties, such as representation and the validation of knowledge, that continue to plague the field of machine learning (Forsyth 1989, Thornton 1992, Johnson-Laird 1993). Second, human and computer capabilities are in many respects complementary (Figures 17 and 18). Human capabilities are particularly strong in areas such as communication, symbolic reasoning, conceptualization, learning, and intuition. We are able to store and adapt experience and quickly grasp the overall picture of even fairly chaotic situations. Our ability to match patterns is applicable not only to visual stimuli but also to abstract concepts and intuitive notions. However, although the biological bases of our cognitive abilities are massively parallel, our conscious reasoning capabilities are essentially sequential. Therefore, large volumes of information and multi-faceted decision contexts tend to easily overwhelm human decision-makers.

When such an overload occurs we tend to switch from an analysis mode to an intuitive mode in which we have to rely almost completely on our ability to develop situation awareness through abstraction and conceptualization. While this is our greatest strength it is also potentially our greatest weakness. At this intuitive meta-level we become increasingly vulnerable to emotional influences that are an intrinsic part of our human nature and therefore largely beyond our control.

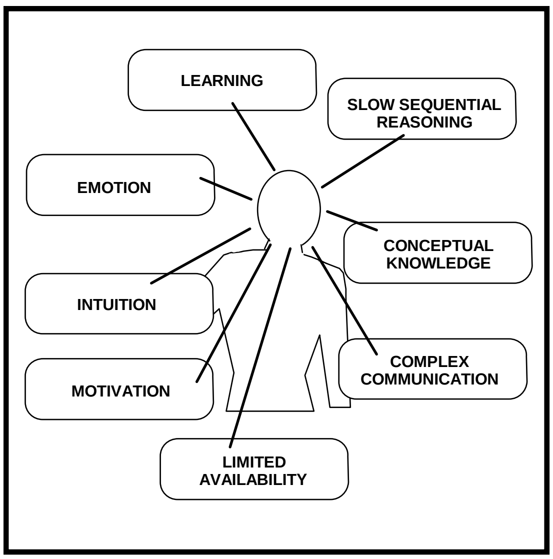

Figure 17: Human abilities and limitations

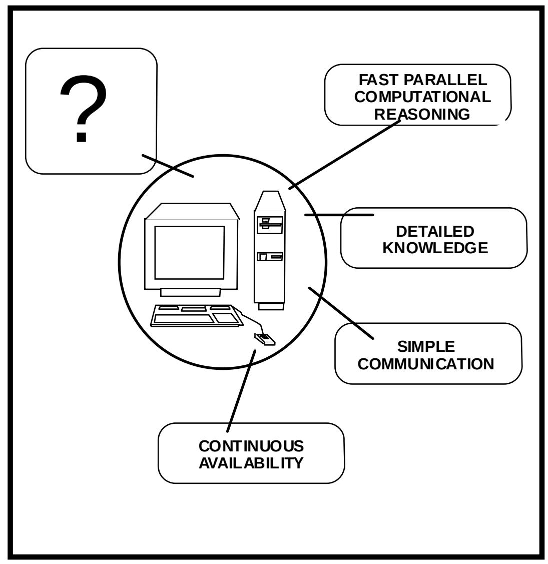

Figure 18: Computer abilities and limitations

The capabilities of the computer are strongest in the areas of parallelism, speed and accuracy (Figure 18). Whereas the human being tends to limit the amount of detailed knowledge by continuously abstracting information to a higher level of understanding, the computer excels in its almost unlimited capacity for storing data. While the human being is prone to making minor mistakes in arithmetic and reading, the computer is always accurate. A slight diversion may be sufficient to disrupt our attention to the degree that we incorrectly add or subtract two numbers. However, if the error is large we are likely to notice that something is wrong further downstream due to our ability to apply conceptual checks and balances. The computer, on the other hand, cannot of its own accord (i.e., at the hardware level) distinguish between a minor mistake and a major error. Both are a malfunction of the entirely predictable behavior of its electronic components. However, at the software level it is possible to provide a layer of automatic reasoning capabilities (i.e., collaborating agents) served by an underlying information model (i.e., ontology). Software with such embedded capabilities is able to draw inferences leading to more sophisticated human-like conclusions.

The differences between the human being and the computer are fundamental. All of the capabilities of the digital computer are derived from the simple building blocks of *0* and *1*. There is no degree of vagueness here, *0* and *1* are precise digital entities and very different from the massively parallel and largely unpredictable interactions of neurons and synapses that drive human behavior. It is not intuitively obvious how to create the high level representations of real world objects (e.g., ship, aircraft, dog, house, power, security, etc.) that appear to be a prerequisite for reasoning and learning capabilities, in a digital computer. While these objects can be fairly easily represented in the computer as superficial visual images (in the case of physical objects such as aircraft, weapons and buildings) and data relationships (in the case of conceptual objects such as power and security) that in itself does not ensure that the computer has any understanding of their real world meaning. These representations are simply combinations of the basic digital building blocks that model, at best, the external shell rather than the internal meaning of the object.

In this respect the term *information-centric* refers to the representation of information in the computer, not to the way it is actually stored in a digital machine. This distinction between *representation* and *storage* is important, and relevant far beyond the realm of computers. When we write a note with a pencil on a sheet of paper, the content (i.e., meaning) of the note is unrelated to the storage device. A sheet of paper is designed to be a very efficient storage medium that can be easily stacked in sets of hundreds, filed in folders, bound into volumes, folded, and so on. However, all of this is unrelated to the content of the written note on the paper. This content represents the meaning of the sheet of paper. It constitutes the purpose of the paper and governs what we do with the sheet of paper (i.e., its use). In other words, the nature and efficiency of the storage medium is more often than not unrelated to the content or representation that is stored in the medium.

In the same sense, the way in which we store bits (i.e., *0s* and *1s*) in a digital computer is unrelated to the meaning of what we have stored. For a computer to interpret data it requires an information structure that provides at least some level of *context*. This can be accomplished utilizing an ontology of objects with characteristics and a rich set of relationships to create a virtual version of a real world situation. The resultant level of information representation is normally adequate to provide the context within which agent logic can automatically operate.

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